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What's Wrong with Understanding Variation Using a Single-Geographic Scale? A Multilevel Geographic Assessment of Life Expectancy in the United States

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Abstract

There has been limited effort to consider multiple areal units or scales in understanding spatial and geographic processes. Treating observed differences in the results by choice of geographic unit of analysis simply as a nuisance is conceptually problematic and can be empirically misleading. We consider the existing research on geographic variations in life expectancy in the United States to demonstrate that prior county-level studies have overestimated the importance of the county level by omitting states. Future investigations should critically assess the relative importance of multiple geographic, spatial, and non-geographic contexts, including an assessment of what units/scales have been omitted.

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Keywords: Geographical variances; Multilevel modeling; Scales; Unit of analysis; Modifiable Area Unit Problem; Life expectancy; United States.

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1. Introduction

The sensitivity of geographic patterns to the choice of areal units is well known, and is commonly captured within the influential framework of "Modifiable Areal Unit Problem" (MAUP)[1], which highlights the fact that areal units are usually arbitrarily determined and, therefore, "modifiable", in the sense that they can be aggregated to form units of different sizes or spatial arrangements leading to different results[1]. The general idea that patterns and relationships observed at one analytical unit (whether individual or geographic/ecological) is well recognized[2,3]. The fundamental premise in these frameworks is that there intrinsically exists one ideal unit of analysis and inference; be it individual or one particular geographic scale[4,5]. With the advent of multilevel modeling[3,6-8], while there has been substantial efforts to simultaneously consider, especially the scales or units of individual and certain geographic aggregation[4,5,9], efforts to consider multiple geographic units/scales has been limited[10,11].

Meanwhile, the idea of considering geographic aggregation at multiple units was explicitly recognized by Harold Moellering and Waldo Tobler in their classic paper published in 1972 entitled, "Geographical Variances"[12]. In their paper, Moellering and Tobler went on to propose a methodological framework to simultaneously model variation at multiple geographic levels[12], outlining what can be considered as a precursor to the current multilevel models. Building on the foundational, but unfortunately less remembered, contribution of Moellering and Tobler, we present the thesis that treating observed differences in the results by choice of unit of analysis simply as a nuisance is conceptually problematic and can be empirically misleading (at worst) and in many instances provide an impoverished interpretation of the undertaken inquiry.

In order to exemplify our thesis, we consider the existing research on geographic variations in life expectancy in the United States (US). Extensive evidence shows increasing geographic disparity in premature mortality trends, indicating that not all areas have equally benefited from the economic and medical improvements. While the all-cause death rates in the US have reduced by 42.9% between 1969 and 2013[13], this national trend alone is inadequate to capture specific states and counties that are performing significantly differently. Substantial variation in life expectancy has been reported across the states[14, 15]. Many more studies have examined life expectancy at the county-level, which is the smallest unit for which mortality data are routinely available in the US, and have reported that between-county inequality has been steadily increasing in recent decades[16-18].

A distinct feature of existing assessments of geography of life expectancy in the US is an exclusive reliance on a single level - either at the state or county - as the unit of analysis. By focusing on a single geographic scale, prior studies have implicitly and/or explicitly treated their unit of interest as the primary driver of variability in life expectancy. For instance, in the county-level analyses, an implicit assumption is that the lowest level at which data is available equates with the appropriate unit of analysis. However, the relative importance of one unit can be truly examined only when multiple scales that are thought to influence the outcome are simultaneously considered[9,10]. Legislations, policies and programs that provide health care, economic assistance and social services are administered and implemented at both the county and state levels. Hence, the significant variation in mortality at the county level, as identified in previous county-level studies, may substantially attenuate once the county-state membership is explicitly modeled.

2. Methods

We used the publicly available county-level life expectancy estimates for 1961–1999 compiled by Ezzati and colleagues for the empirical exemplification[16]. The analytic data contains repeated cross-sections of 122,850 life expectancy estimates across 39 years at level-1, nested within 3,150 counties at level-2, nested within 51 states at level-3. We specified and estimated the following models. First, we ignored states and assumed repeated measurements of life expectancy to be nested only within counties (Model 1). We then estimated models ignoring counties and specified repeated measures to be nested within only states (Model 2). Lastly, we estimated a three-level model accounting for the entire hierarchical nesting structure of repeated measures in counties in states (Model 3). In order to visualize the geography of life expectancy by counties and states, we mapped the residuals estimated from each of the models. Technical details and interpretations of each of the models are provided in Appendix A.

3. Results

From 1961-1999, life expectancy in the US increased from 66.9 to 73.6 years for men and from 73.9 to 79.3 years for women, but this increase did not follow a linear trend. Estimates of the mean life expectancy did not differ substantially across the three models.

In the two-level model that ignored the states (Model 1), counties accounted for 84.5% (σ_{u0}^2=4.0 (SE: 0.1)) of the total variability in life expectancy for men and 78.6% for women (σ_{u0}^2=2.3 (SE: 0.06)), conditional on the secular trend over time. When the county membership was ignored (Model 2), states accounted for more than half (55.0%; σ_{v0}^2=3.1 (SE: 0.6)) of the variation in men and less than half (47.0%; σ_{v0}^2=1.5 (SE: 0.3)) in women (Table 1). The within-county-between-time, variation in life expectancy was much larger than the within-state-between-time variation. For men, only 15.5% (σ_{e0}^2=0.7 (SE: 0.003)) of the variability was attributable to time in Model 1, whereas 45% (σ_{e0}^2=2.5 (SE: 0.01)) was attributed to time in Model 2. Similar pattern was observed for women (Table 1).

Table 1. Variance estimates (VE) (standard errors (SE)) and proportion of variation (%VPC) in life expectancy in the United States attributable to state-, county-, and time-units based on different multilevel model specifications

	State		County		Time		Total	
	VE (SE)	% VPC	VE (SE)	% VPC	VE (SE)	% VPC	VE	% VPC
Male								
Model 1	-	-	3.978 (0.101)	84.5%	0.727 (0.003)	15.5%	4.705	100%
Model 2	3.066 (0.604)	55.0%	-	-	2.510 (0.010)	45.0%	5.577	100%
Model 3	2.419 (0.494)	48.8%	1.814 (0.047)	36.6%	0.727 (0.003)	14.7%	4.961	100%
Female								
Model 1	-	-	2.290 (0.058)	78.6%	0.625 (0.003)	21.4%	2.915	100%
Model 2	1.524 (0.301)	47.0%	-	-	1.717 (0.007)	53.0%	3.241	100%
Model 3	1.226 (0.252)	41.4%	1.112 (0.029)	37.5%	0.625 (0.003)	21.1%	2.962	100%

Model 1: Time (level-1) nested within county (level-2); Model 2: Time (level-1) nested within state (level-2); Model 3: Time (level-1) nested within county (level-2) and state (level-3)

Compared to the results from two-level models, the proportion of variation attributable to counties and states was substantially different for the three-level model. For men and women, between-county variation in life expectancy was less than half of what was found in Model 1 and between-state variation also attenuated compared to Model 2. Of the total variation in life expectancy for men, counties accounted for 36.6% (σ_{u0}^2=1.8 (SE: 0.05)) and states accounted for 48.8% (σ_{v0}^2=2.4 (SE: 0.5)). Similarly, for women, when both geographic scales were simultaneously modeled, counties accounted for 37.5% (σ_{u0}^2=1.1 (SE: 0.03)) and states accounted for 41.4% (σ_{v0}^2=1.2 (SE: 0.3)) of the total variation in life expectancy (Table 1).

Although the pattern in variance decomposition was largely consistent by sex, the magnitude of total variation in life expectancy was much larger for men compared to women. For instance, accounting for both county and state memberships, life expectancy varied from 62.5 to 71.3 years for men and from 70.5 to 77.3 years for women in the referent year (1961). The observed difference in the variation was largest at the state level, with the between-state variation being two times larger for men than that for women (Table 1).

Based on Model 1, 1,200 counties (38.1%) for men and 1,226 counties (28.9%) for women were identified as having life expectancy significantly lower than the average, whereas 1,529 counties (48.5%) for men and 1,482 counties (45.3%) for women were identified as having life expectancy significantly higher than the average (Table 2). The remaining 421 (13.37%) counties for men and 496 (15.75%) counties for women were not statistically different from the overall US means for men and women, respectively. Put differently, these counties can be considered as the “typical” or “average” counties. Figures 1A and 2A show that low life expectancy counties were concentrated in the Southeast, while high life expectancy counties were concentrated in the Midwest and Northeast for men and women (Figures 1, 2). When state membership was accounted for, the number of low and high life expectancy counties reduced substantially and the number of average counties more than doubled. From Model 3, 970 counties (30.79%) for men and 1,048 counties (33.27%) for women were considered to be within the bounds of national average life expectancy level, conditional on the states (Table 2).

Table 2. US counties and states with statistically significantly high and low life expectancies based on different multilevel model specification

	Male			Female		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
Counties, N (%)						
Low life expectancy	1,200 (38.1%)		1,078 (34.22%)	1,226 (38.92%)		997 (31.65%)
Average life expectancy	421 (13.37%)		970 (30.79%)	496 (15.75%)		1,048 (33.27%)
High life expectancy	1,529 (48.54%)		1,102 (34.98%)	1,428 (45.33%)		1,105 (35.08%)
States, N (%)						
Low life expectancy		16 (31.37%)	14 (27.45%)		17 (33.33%)	15 (29.41%)
Average life expectancy		12 (23.53%)	18 (35.29%)		14 (27.45%)	20 (39.22%)
High life expectancy		23 (45.1%)	19 (37.25%)		20 (39.22%)	16 (31.37%)

Model 1: Time (level-1) nested within county (level-2); Model 2: Time (level-1) nested within state (level-2); Model 3: Time (level-1) nested within county (level-2) and state (level-3)

When repeated measurements were assumed to be nested within states only (Model 2), 16 states for men and 17 states for women were classified as having life expectancy significantly below the national average. Further, 23 states for men and 20 states for women were identified as high life expectancy states (Table 2). In general, low life expectancy states were concentrated in the Southeast, whereas high life expectancy states tended to be in the West and Midwest (Figures 1C, 2C). For both men and women, District of Columbia, South Carolina and Mississippi were among the states that had the shortest longevity, while Hawaii, Minnesota and Iowa were among the states that consistently ranked the highest life expectancy (Appendix B). However, changes in the ranking and classification of the states occurred when the county unit was added, such that only 14 states remained to be statistically significantly lower than the average life expectancy and only 19 were classified as significantly higher than the average for men (Table 2). Moreover, 15 states were classified as low life expectancy states and 16 were classified as high life expectancy states for women in Model 3 (Table 2).

Further, the county and state maps from two- and three-level models (Figures 1, 2) clearly showed that geographic variation in life expectancy in the US cannot be sufficiently summarized in a single map. Once states and counties were modeled simultaneously, clustering of high and low life expectancy counties was much more nuanced, as shown in Figures 1B and 2B. Indeed, one can develop a typology based on county and state "highs" and "lows". Within the same state, both low and high life expectancy counties coexisted. This has important implications because low life expectancy counties nested within high life expectancy states need to be treated differently from low life expectancy counties nested within low life expectancy states. Hence, Figures 1, 2B and 1, 2D from Model 3 should be considered together for a complete and accurate visualization of geographic variation in life expectancy for men and women (Figures 1, 2).

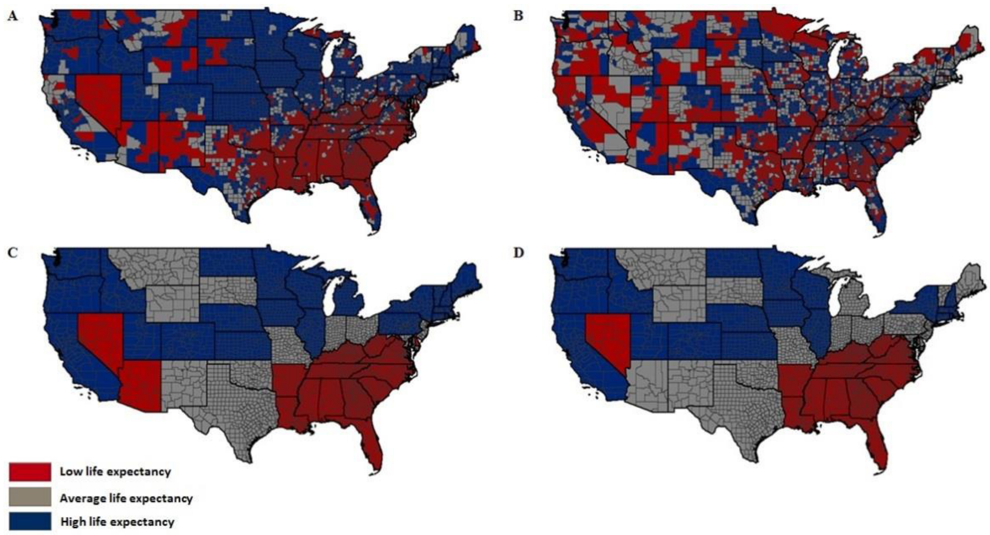

Figure 1. Visualizing counties and states with statistically significantly high and low male life expectancies based on different multilevel model specifications *(A) County map when states are ignored; (B) County map when states are accounted for; (C) State map when counties are ignored; (D) State map when counties are accounted for*

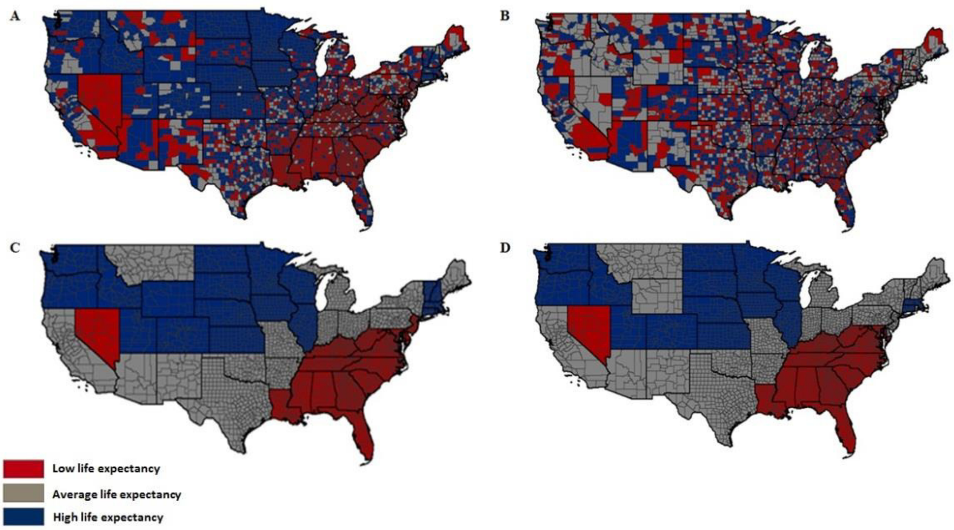

Figure 2. Visualizing counties and states with statistically significantly high and low female life expectancies based on different multilevel model specifications *(A) County map when states are ignored; (B) County map when states are accounted for; (C) State map when counties are ignored; (D) State map when counties are accounted for*

4. Discussion

Drawing from the above empirical exemplification of geographic variations in life expectancy in the US, we discuss four key scientific considerations for future research.

First, we demonstrated that states are as, if not more, important than counties in shaping the geographic variability in life expectancy in the US. Yet prior studies have largely focused on describing the inequality across counties[16,17,19] and persistent clustering of high and low mortality counties[20]. In doing so, such studies have implicitly suggested that research and policy efforts should focus on the county-level processes and causes that might be the only drivers of longevity and premature mortality. We found that while counties accounted for 85% and 79% of the total variability in life expectancy for men and women, respectively, they accounted for less than 40% when states and counties were simultaneously modeled. This suggests that prior literature has considerably overestimated the importance of counties by omitting states. When geographic processes are likely to occur at multiple scales, empirical assessments should expand the units of analysis to accurately understand the scale at which action lies. While prior county-level studies have narrowly focused on a single map of geography of life expectancy (such as Figures 1, 2A), we argue that Figures 1, 2B and 1, 2D should be considered together for a complete and accurate visualization of geography of life expectancy.

Second, there is a tendency – for no obvious reason that we are aware (except to consider geographic aggregations as a "proxy" for individuals) – to assume that a finer resolution of geographic aggregation (e.g., counties) is more important than a coarser resolution (e.g., states). However, we found that after accounting for counties, almost 50% of the total variation in life expectancy for men and over 40% for women were attributable to states. In fact, literature supports that processes at both state and county levels independently and simultaneously drive patterns of longevity and premature mortality. For instance, state and local social spending[21], health care resources[22,23], income inequality[24-26] and other social environmental determinants[27] are suggested to affect premature mortality. Therefore, unless based on well-grounded theory and mechanistic explanations, finer resolution should not be automatically assumed as the more important scale. Most pertinently, it would be impossible to assess the relative importance of either the finer or coarser geographic scale by studying only one or the other.

Third, we visualized geographic clustering at the state and county scales, conditional on each other, and we argue that this is not a "nuisance" to be simply accounted for. When geographic clustering is detected, it is not uncommon to identify it as a violation of the assumption of independent residuals that needs to be corrected by driving the *Moran's I* (a summary statistic for quantifying "spatial clustering") to 0. However, such clustering should be seen as a substantively important pattern that merits careful exploration. For instance, states and counties with life expectancy statistically significantly below the average were concentrated in the South. From a historical perspective, this variation in current life expectancy may be long lasting health consequences of Jim Crow laws, which legally permitted racial discrimination in the Southern states[28,29]. Similarly, there may be other important inter-county and inter-state processes driving geographic clusters of high and low life expectancy.

Finally, the total variation in life expectancy was much larger for men compared to women, with the between-state variation being two times larger for men. It is well known that women, on average, live longer than men; what's less reported and understood is that while men, on average live shorter lives, they are also highly variable. Though this phenomenon of differential variance for men and women is often overlooked, this may be indicating potential interaction effects of a geographic phenomenon by sex or presence of differential sex-specific geographic processes driving geographies of life expectancy. Anticipating heterogeneity by sex, and perhaps by other sociodemographic and economic characteristics, has important implications for policies and interventions, and therefore should be explicitly hypothesized and investigated in future multilevel studies.

The primary goal of this essay was to use existing research on geographic variations in life expectancy in the US to illustrate that exclusive focus on one geographic scale, while omitting other levels, may lead to partial or biased conclusions. There are several important issues to consider when interpreting our findings. For the sake simplicity, we restricted to a "hierarchical" conceptualization of geographic units at multiple units or scales. However, other non-hierarchical extensions that recognize, for instance, the importance of both geographic *and* spatial phenomenon have been discussed elsewhere[30]. Furthermore, extending to other non-geographic contexts such as schools[31] should also be routinely considered when possible and appropriate. Finally, critical other units or scales, including individual and residential environments, were not considered in our analysis since these were not available.

5. Summary

An inquiry focused on understanding the importance of geographic processes can no longer offer a comprehensive picture unless multiple geographic (or for that matter non-geographic) units or scales that influence the outcome are considered simultaneously. Indeed, anticipating such complexity in our modeling is only appropriate because the real world – more often than not – tends to reflect such complexities. In the field of social epidemiology, for instance, theories and empirical evidence support that variation in health is *simultaneously* shaped by personal attributes, micro geographic environments (e.g., neighborhoods or communities), macro geographic environments (e.g., states, countries), and other non-geographic but equally important social groupings (e.g., families, schools, workplaces, health care providers). Given this reality, it can be extremely misleading to assume that there is only one right unit of analysis. Empirical assessments of geographic variation in any outcomes should no longer be restricted to a single-level perspective. Instead, future investigations should critically assess the relative importance of multiple geographic, spatial, and non-geographic contexts, including an assessment of what units/scales have been omitted or cannot be observed.

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Appendix A. Technical details and interpretation of multilevel models

All of the following models were stratified by sex and adjusted for years as fixed effects. We used MLwiN 2.34 software to obtain all estimates, and ArcGIS to generate the maps.

A.1. Model 1: County only

We first fit a two-level model in which repeated measurements of life expectancy over time i are nested within county j: $Life\ Expectancy_{ij} = \beta_0 + \beta_t year_{ij} + (e_{0ij} + u_{0j})$. The parameter β_0 represents the life expectancy for year 1961 and β_t represents a vector of coefficients measuring the differentials in life expectancy for each year t compared to the referent year. Residual differentials for county j (ie. u_{0j}) and measurement i (ie. e_{0ij}) are each assumed to be independent and normally distributed with a mean of 0 and a variance of σ^2_{u0} and σ^2_{e0}, which respectively quantifies the between-county and between-time variation in life expectancy, conditional on the secular changes in life expectancy over time. Based on these estimates, the proportion of variation in life expectancy attributable to the county unit can be calculated as $\sigma^2_{u0}/(\sigma^2_{u0} + \sigma^2_{e0})$.

A.2. Model 2: State only

Next, we ignore the county membership and fit a two-level model in which repeated measurement i are nested within state k: $Life\ Expectancy_{ik} = \beta_0 + \beta_t year_{ik} + (e_{0ik} + v_{0k})$. Here, the between-state variation in life expectancy, conditional on the fixed effects of time, is estimated as σ^2_{v0} from a set of residual differentials for state k (ie. v_{0k}), and the proportion of variation attributable to the state level is calculated as $\sigma^2_{v0}/(\sigma^2_{v0} + \sigma^2_{e0})$.

A.3. Model 3: County and state

In the final model, we estimate a three-level model for measurement i in county j and state k: $Life\ Expectancy_{ijk} = \beta_0 + \beta_t year_{ik} + (e_{0ijk} + u_{0jk} + v_{0k})$. Interpretations for the fixed coefficients and random effects are the same as above. The variance estimates and proportion of variation attributable to the county and state units can now be calculated simultaneously.

A.4. Mapping geographic differences at multiple levels

Based on a set of county-level residuals (u_{0j}) estimated from *Model 1*, counties with residuals within the 95% coverage bounds of the average life expectancy are classified as 'average' counties (in gray). Similarly, counties with residuals that deviate statistically significantly below the average (ie. (u_{0j} ± 1.96*standard deviation < 0) are denoted with red, and those that deviate above the average (ie. (u_{0j} ± 1.96SD) > 0) are denoted with blue. The same procedure is repeated for state-level residuals (v_{0k}) estimated in *Model 2,* and for u_{0j} and v_{0k} estimated in *Model 3*.

Appendix B. List of US states with statistically significantly high and low life expectancies based on different multilevel model specification (ordered from lowest to highest life expectancy)

	Male		**Female**	
	Model 2	*Model 3*	*Model 2*	*Model 3*
Low life expectancy	District Of Columbia, South Carolina, Mississippi, Georgia, Alabama, Louisiana, North Carolina, Nevada, Tennessee, West Virginia, Kentucky, Virginia, Florida, Arkansas, Delaware, Arizona	District Of Columbia, South Carolina, Mississippi, Georgia, Alabama, Louisiana, North Carolina, Nevada, Tennessee, West Virginia, Kentucky, Virginia, Florida, Arkansas	District Of Columbia, South Carolina, Mississippi, Louisiana, Georgia, Alabama, Nevada, West Virginia, Delaware, North Carolina, Maryland, Alaska, Kentucky, Virginia, New Jersey, Tennessee, Florida	District Of Columbia, South Carolina, Mississippi, Louisiana, Georgia, Alabama, Nevada, West Virginia, North Carolina, Maryland, Kentucky, Alaska, Virginia, Tennessee, Florida
Average life expectancy	New Mexico, Oklahoma, Alaska, Texas, Maryland, Montana, South Dakota, Missouri, Wyoming, Indiana, Ohio, New Jersey	Delaware, Arizona, New Mexico, Oklahoma, Alaska, Texas, Maryland, Montana, South Dakota, Missouri, Wyoming, Indiana, Ohio, New Jersey, Pennsylvania, Michigan, Maine, Vermont	Arkansas, Ohio, Pennsylvania New York, Arizona, Michigan, New Mexico, Indiana, Maine, Oklahoma, Texas, California, Montana, Missouri	Delaware, New Jersey, Arkansas, Ohio, Pennsylvania, New York, Arizona, Michigan, Indiana, New Mexico, Maine, Oklahoma, Texas, California, Montana, Missouri, New Hampshire, Wyoming, Vermont, Rhode Island
High life expectancy	Pennsylvania, Michigan, Maine, New York, Illinois, California, Vermont, New Hampshire, Oregon, Colorado, Idaho, Massachusetts, Washington, North Dakota, Kansas, Wisconsin, Utah, Connecticut, Rhode Island, Nebraska, Iowa, Minnesota, Hawaii	New York, Illinois, California, New Hampshire, Oregon, Idaho, Colorado, Massachusetts, Washington, North Dakota, Kansas, Rhode Island, Connecticut, Wisconsin, Utah, Nebraska, Iowa, Minnesota, Hawaii	New Hampshire, Illinois, Wyoming, Vermont, South Dakota, Oregon, Massachusetts, Washington, Rhode Island, Idaho, Utah, Connecticut, Colorado, Wisconsin, Kansas, North Dakota, Nebraska, Iowa, Minnesota, Hawaii	Illinois, South Dakota, Oregon, Massachusetts, Washington, Connecticut, Utah, Idaho, Colorado, Wisconsin, Kansas, North Dakota, Nebraska, Iowa, Hawaii, Minnesota

Model 2: Time (level-1) nested within state (level-2); Model 3: Time (level-1) nested within county (level-2) and state (level-3)